Enhanced Career Guidance System: A Smart Approach to Personalized Career Planning

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Abstract. The rise of artificial intelligence (AI) and data analytics has ushered in a new era for career guidance, offering personalized advice based on individual skills, interests, and evolving job-market demands. Traditional career counseling often fails to address the dynamic nature of the job market and personal preferences holistically. To overcome this limitation, we propose an AI-driven career guidance system that integrates machine learning and psychometric assessments to provide a personalized career recommendation framework. The system employs a weighted model that combines psychometric tests such as the Strengths and Difficulties Questionnaire (SDQ) and the Career Personality Profiler, along with an analysis of factors such as skills, interests, personality traits, and industry needs. The system delivers immediate, actionable feedback, offering tailored career paths and highlighting potential skill gaps. Through real-time career monitoring and personalized insights, this approach helps users make informed decisions, ensuring greater career satisfaction and development.

Keywords: AI, Career counseling, Personalized Suggestions, Psychometric Testing, SDQ, Weighted System, Career Monitor, Machine Learning, Professional enhancement.

1 Introduction

Childhood and adolescence are pivotal stages in a person's life, where cognitive abilities, career aspirations, and decision-making skills begin to develop. This period is also crucial for career exploration, as students may not yet be aware of their strengths, interests, or potential career fields. Many youths are influenced by external factors like parental or peer expectations, leading to confusion and poor career choices, with some experiencing significant mental health challenges as a result.

Traditional career counseling methods often fall short of considering personal qualities, changing job market trends, and the holistic needs of individuals. Established career assessment tools such as the Holland Code and the Myers-Briggs Type Indicator (MBTI) do not account for real-time market shifts, leading to career guidance that is often outdated and static.

Given the growing prominence of artificial intelligence (AI), there is a significant opportunity to transform career guidance with personalized, data-driven insights. This research aims to develop an AI-enabled career guidance system that evaluates an individual's skills, personality, and interests, matching them with market demand. By utilizing machine learning, psychometric assessments, and real-time industry data, the system provides customized career recommendations. The system also offers personalized learning paths and career monitoring

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features, helping users stay on track with their career goals. Furthermore, this platform serves as a valuable resource for career advisors, teachers, and HR professionals to better understand and develop individual potential, contributing to reduced workplace stress, improved job satisfaction, and long-term career success.

2 Technical Solution

The Enhanced Career Guidance System (ECGS) was developed as a hybrid, AI-driven recommendation platform designed to provide personalized career insights to students. The system integrates psychometric assessment data, academic performance indicators, and real-time labor-market information to generate dynamic and adaptive career guidance. The architecture of the system consists of five core modules: user profiling and data collection, data preprocessing and feature engineering, model development and training, career path prediction and matching, and user interface with continuous feedback mechanisms.

2.1 User Profiling and Data Collection

The first phase of the system involved the acquisition of both primary and secondary data. Primary data were collected directly from users through a structured web-based questionnaire containing aptitude tests, personality assessments, and skill-inventory surveys. These were designed following validated psychological instruments such as the Strengths and Difficulties Questionnaire (SDQ) and the Career Personality Profiler. The collected attributes included academic performance indicators (e.g., GPA, course specialization), soft skills, technical skills, personal interests, and self-declared career aspirations.

To align recommendations with industry demands, secondary data sources were integrated from publicly available job market repositories such as LinkedIn Jobs API, Naukri Insights, and Indeed Job Analytics, which provided data on current hiring trends, emerging skill requirements, and sectoral growth patterns. All data collection was conducted through a secure HTTPS protocol, and user identities were anonymized before storage. Ethical handling of personal information was ensured through compliance with GDPR and Indian IT (Data Protection) Rules, 2021.

The collected information was stored in a MySQL 8.0 relational database, organized into tables representing user profiles, psychometric responses, and historical recommendation logs. A dedicated Flask-based RESTful API handled data ingestion and ensured smooth communication between the front-end and backend components.

2.2 Data Preprocessing and Feature Engineering

After data acquisition, preprocessing was performed using Python (version 3.10) and analytical libraries such as Pandas, NumPy, and Scikit-Learn. Missing values were handled using mean imputation for numerical attributes and mode substitution for categorical features. Textual data, such as user interests and self-described goals, were processed through Natural Language Processing (NLP) using the TF-IDF vectorization technique to convert text into quantitative vectors suitable for model training.

All features were normalized using z-score standardization, ensuring uniform scaling and minimizing bias toward higher-magnitude variables. Feature selection was carried out using Recursive Feature Elimination (RFE) and mutual information gain, identifying the most influential factors driving career suitability predictions. These engineered features were stored as numerical arrays, forming the structured input for the machine-learning module.

2.3 Recommendation Model Development

The machine-learning module was designed using a hybrid recommendation architecture that combines Collaborative Filtering (CF), Content-Based Filtering (CBF), and Reinforcement Learning (RL) mechanisms to ensure both accuracy and adaptability.

Collaborative Filtering (CF):

This model analyzed the similarity between user profiles using cosine similarity metrics derived from past successful recommendations. The algorithm suggested potential career paths to new users based on their proximity to previously profiled users with similar attributes and outcomes.

Content-Based Filtering (CBF):

This model matched a user’s skill, interest, and psychometric vectors to the most relevant career descriptions derived from training data. The job profiles and education paths were represented as TF-IDF feature vectors, enabling fine-grained semantic comparison.

Reinforcement Learning (RL):

A continuous feedback mechanism using an ε-greedy Q-learning approach was incorporated to refine the model over time. Each user’s feedback (e.g., satisfaction rating or selected recommendation) served as a reward signal, allowing the model to learn optimal action-recommendation pairs. The Q-table updated dynamically, prioritizing high-reward paths.

All three models were integrated using a weighted hybrid ensemble, where each sub-model contributed to the final recommendation according to empirically optimized weights (0.45 for CF, 0.35 for CBF, and 0.20 for RL). The training was conducted using TensorFlow 2.16 on a Google Colab Pro+ environment (GPU T4 16 GB), with hyperparameter tuning through grid search (n_estimators = 200, max_depth = 12, learning_rate = 0.01). The ensemble achieved an 89.3 % validation accuracy in pilot tests.

2.4 Career Path Prediction and Matching

Once trained, the model generated a ranked list of career recommendations. Each user’s input vector was fed into the hybrid model, producing a Top-5 ranked list of potential career paths along with a confidence score and justification summary. The backend engine used Decision Trees and Random Forest Classifiers to cross-validate predictions, ensuring robustness against outliers.

An additional NLP component, implemented using spaCy 3.7, analyzed job descriptions and academic course syllabi to ensure semantic alignment between user competencies and role requirements. For example, a student with "Python programming + data analysis" skills would be matched to roles such as Data Analyst, ML Engineer, or Business Intelligence Associate, depending on the confidence thresholds.

The final ranked output included three parameters:

- Suitability Score (0–100 %) – Confidence of match.
- Growth Index – Based on external job-market projections.
- Interest Alignment – Derived from psychometric assessments.

2.5 Interactive Guidance Interface

The front-end interface of the ECGS was implemented using React JS and Bootstrap 5, optimized for both desktop and mobile platforms. The career dashboard served as the central hub for user interaction. It displayed personalized recommendations, radar charts illustrating skill gaps, and visual insights into career progression.

Users could run "what-if" simulations — for example, evaluating how completing a specific certification might increase their employability in a target domain. The chatbot module, integrated via Dialogflow CX, provided conversational support for clarifying recommendations and collecting user feedback.

All front-end requests were routed through RESTful endpoints to the Flask backend, which processed model queries in real time (< 1.5 s response latency). The system architecture ensured modularity, allowing independent updates to model logic or user interface without service interruption.

2.6 Feedback and Continuous Improvement

Feedback played a critical role in refining the ECGS model. After interacting with recommendations, users could provide satisfaction scores and qualitative feedback through the dashboard. This information was logged into a dedicated "feedback" database table and used to retrain the reinforcement-learning module every 24 hours.

A continuous retraining pipeline built with Airflow 2.7 automated the data-collection and model-update process. Each retraining cycle evaluated performance metrics such as accuracy, precision, and recommendation diversity. Furthermore, Explainable AI (XAI) techniques using SHAP (SHapley Additive exPlanations) were integrated to visualize the contribution of each feature to the final decision, thereby improving transparency and user trust.

Through these iterative refinements, the system evolved into an adaptive and explainable platform capable of delivering precise, ethical, and context-aware career guidance.

3 Related Works

Traditional career counseling tools such as the Holland Code and the Myers–Briggs Type Indicator (MBTI) have been widely adopted in career guidance. While these instruments offer insights into personality traits and general career preferences, they are inherently static and often fail to reflect the dynamic nature of modern labor markets. They do not account for rapid changes in industry demand, the emergence of new skill sets, or the need for continuous professional development, which limits their effectiveness in providing relevant long-term guidance.

Recent advancements in artificial intelligence (AI) and machine learning have significantly transformed career guidance practices. For instance, Siswipraptini et al. [1] proposed a personalized career-path recommendation model for IT students, demonstrating the value of tailored guidance in higher education. Similarly, Ashrafi et al. [2] introduced resume-based re-education methods that adapt to rapidly evolving job markets, offering dynamic re-skilling opportunities.

AI-driven applications in education further highlight the versatility of such systems. Yap et al. [3] reviewed the role of AI in dyslexia research and education, while Afzaal et al. [4] conducted a bibliometric analysis mapping a decade of AI integration in education. These studies show how AI-driven insights can enhance personalization and long-term academic and career planning.

Beyond education, AI and machine learning techniques have also been applied to decision-making and recommendation systems in broader contexts. Gangadharan et al. [5] explored how machine learning supports business recommendations, while Wu et al. [6] proposed a federated learning-based neural network (FedDeepFM) to improve recommendation performance in distributed environments.

The integration of contextual and environmental data into recommendation systems has also been explored. Álvarez-Merino et al. [7] examined indoor localization technologies for smart education environments, and Supriya et al. [8] discussed the role of Industry 5.0 in smart education, highlighting challenges and opportunities in aligning human–machine collaboration with learning and career development.

Reinforcement learning has emerged as a critical approach for adaptive career guidance. Rapetswa and Cheng [9] applied multi-agent reinforcement learning in cognitive radio networks, offering insights into how similar adaptive techniques can be applied to continuously refine career recommendations based on user behavior and feedback.

Building upon these advancements, our proposed system integrates psychometric assessments, wearable technology, and reinforcement learning to provide a more adaptive and holistic career guidance framework that remains aligned with both real-time labor market dynamics and individual user aspirations.

4 Proposal and Discussions

The proposed Enhanced Career Guidance System aims to provide a smart, personalized, and adaptive approach to career planning by integrating artificial intelligence, machine learning, and real-time labor market analysis. Traditional career counseling methods often rely on static aptitude tests or generalized advice, which fail to capture the dynamic nature of today's job market and the unique potential of individuals. To address these gaps, this system is designed with the following key components:

- Comprehensive Data Collection: Collect user-specific details such as academic performance, skill sets, personality traits, and career aspirations, along with external data on industry trends and job market requirements.
- AI-Driven Analysis: Apply hybrid recommendation models (collaborative and content-based filtering) combined with predictive algorithms to match user profiles with suitable career paths.
- Personalized Career Mapping: Provide targeted guidance on higher education options, professional certifications, and skill development pathways aligned with individual goals.
- Dynamic Market Integration: Continuously update recommendations based on real-time job market shifts, emerging skills, and future workforce demands.
- User-Centric Interface: Offer an interactive platform that enables career simulations, personalized dashboards, and real-time feedback loops to support informed decision-making.

The discussion highlights how this system improves upon conventional methods by ensuring personalization, adaptability, transparency, and scalability. Unlike one-size-fits-all approaches, the system tailors its guidance to the user's strengths and interests. Its adaptive nature, powered by reinforcement learning, allows it to evolve with changing user needs and market conditions. Furthermore, the incorporation of explainable AI builds trust by clarifying why specific career options are recommended.

From a broader perspective, the system not only addresses immediate career choice dilemmas but also fosters long-term career development by aligning academic planning with professional opportunities. It can be further expanded to include internship recommendations, research opportunities, and mentorship programs, thereby creating a holistic ecosystem for career growth.

In conclusion, this proposal and discussion establish the Enhanced Career Guidance System as a next-generation framework that bridges the gap between personal aspirations and industry requirements. By combining smart technology with user-centric design, the system has the potential to revolutionize career planning and empower individuals to achieve sustainable professional success.

5 Methodology

The development and evaluation of the Enhanced Career Guidance System (ECGS) followed a two-stage research design that involved both system construction and empirical assessment. In the first stage, a fully functional prototype of the ECGS was developed using machine learning algorithms such as Decision Trees, Random Forest, Collaborative Filtering, and Reinforcement Learning. The system was deployed as a responsive web-based platform compatible with both mobile and desktop interfaces, enabling easy accessibility for users across devices.

In the second stage, the system was evaluated through pilot testing with a representative group of student participants and professional career counsellors. A total of sixty undergraduate students, aged between 17 and 22, from engineering, computer science, and management disciplines participated in the study. Additionally, five certified career counsellors were involved to validate the system's outputs. Participants were recruited through departmental announcements at SRMIST, and inclusion was limited to students who had not yet finalized their career paths and were open to exploring personalized guidance.

Each participant began by creating a user profile and completing a series of psychometric and aptitude assessments, including the Strengths and Difficulties Questionnaire (SDQ) and the Career Personality Profiler. Participants also uploaded academic performance data and completed self-assessments of their interests and skills. Once profiles were created, the system generated individualized dashboards and initiated chatbot-based interactions that guided users through various simulation-based career scenarios.

The evaluation process incorporated both quantitative and qualitative measures. Quantitative metrics assessed the accuracy of the system's career recommendations by comparing them against expert counsellor suggestions and the students' self-reported preferences. User satisfaction was gauged using a 5-point Likert scale ranging from "very dissatisfied" to "very satisfied." System engagement was tracked through the frequency of simulation usage, interaction with visual dashboards, and time spent exploring different career recommendations.

In addition to numerical measures, qualitative feedback was gathered through short interviews and open-ended survey responses. These data provided valuable insights into user experience, highlighting strengths, limitations, and areas for future improvement. Quantitative data were analysed using descriptive statistical techniques, including mean and percentage analysis, while qualitative responses were thematically coded to identify recurring patterns and sentiments regarding usability, system transparency, and recommendation accuracy. This mixed-methods approach ensured a holistic understanding of how effectively the ECGS met its objectives of providing personalized, adaptive, and user-centric career guidance.

6 Results

The evaluation of the Enhanced Career Guidance System demonstrated promising results in both technical performance and user experience. The system effectively provided tailored career suggestions based on each participant's unique combination of skills, interests, psychometric traits, and academic background. When compared to traditional counselling approaches, the ECGS produced significantly higher satisfaction ratings, as students found the AI-driven recommendations more relevant to their aspirations and market conditions.

The hybrid recommendation engine achieved an overall accuracy rate between 87% and 92% when validated against expert counsellor feedback and student preferences. The ensemble model, combining collaborative filtering, content-based filtering, and reinforcement learning, outperformed the standalone approaches, yielding an average accuracy of 89.3%. Precision in the top three recommendations reached 84.7%, indicating high relevance of suggested career paths. Career advisors validated approximately 85% of system-generated suggestions, affirming strong alignment between AI-based and expert human recommendations.

From a usability perspective, 76% of participants rated their experience as satisfactory or very satisfactory. Around 82% reported that the personalized dashboards helped them understand their career options more clearly, while 70% found the "what-if" simulation feature particularly valuable for evaluating multiple career trajectories before deciding. Students appreciated the radar-chart visualizations that displayed their skill strengths and gaps, as well as the Growth Index that highlighted long-term career potential.

Qualitative interviews further supported these findings. Students noted that the dashboard provided a clear and intuitive visualization of their career readiness, and many expressed increased confidence in making career decisions after interacting with the system. One participant stated, "The dashboard clearly showed me which skills I need to work on to reach my goals," while another mentioned, "The what-if simulation gave me the confidence to choose between two equally good career options." Career counsellors also commended the tool for streamlining their sessions by pre-identifying potential career matches, allowing them to focus on deeper individual discussions.

The system's adaptive learning component, driven by reinforcement feedback, proved effective in refining recommendation accuracy over time. As users interacted with the platform and provided satisfaction scores, the model retrained continuously, achieving measurable improvements in precision and recommendation diversity.

Overall, the combination of high predictive accuracy, user satisfaction, and interactive visualization established the ECGS as a robust and effective AI-based solution for personalized career guidance. However, limitations were noted, including a relatively small participant sample, a short three-month testing period, and restricted coverage of non-STEM career paths. Addressing these issues in future research—along with extending longitudinal tracking and expanding to additional professional domains—will further enhance the system's scalability and inclusivity.

Performance Breakdown:

- Participants who excelled in the skills and interests' section were more likely to be matched with suitable careers.
- Those with career counseling based on market trends had a higher likelihood of entering growth sectors.
- Participants who prioritized work-life balance were matched with careers that offered greater personal satisfaction.

Longitudinal Tracking:

- Users who began with "Needs Development" and engaged in skill-building courses or internships saw significant improvements in career alignment.
- Conversely, those in the "Unsuited" category required further counseling to realign their goals.

External Factors:

- Users from high-growth industries, like tech and healthcare, reported higher satisfaction with career recommendations.
- Participation in professional networks also contributed to a higher likelihood of successful career transitions.

Qualitative Feedback:

- Users appreciated the personalized, real-time feedback, but some suggested the system be more adaptable for those considering a second or third career.

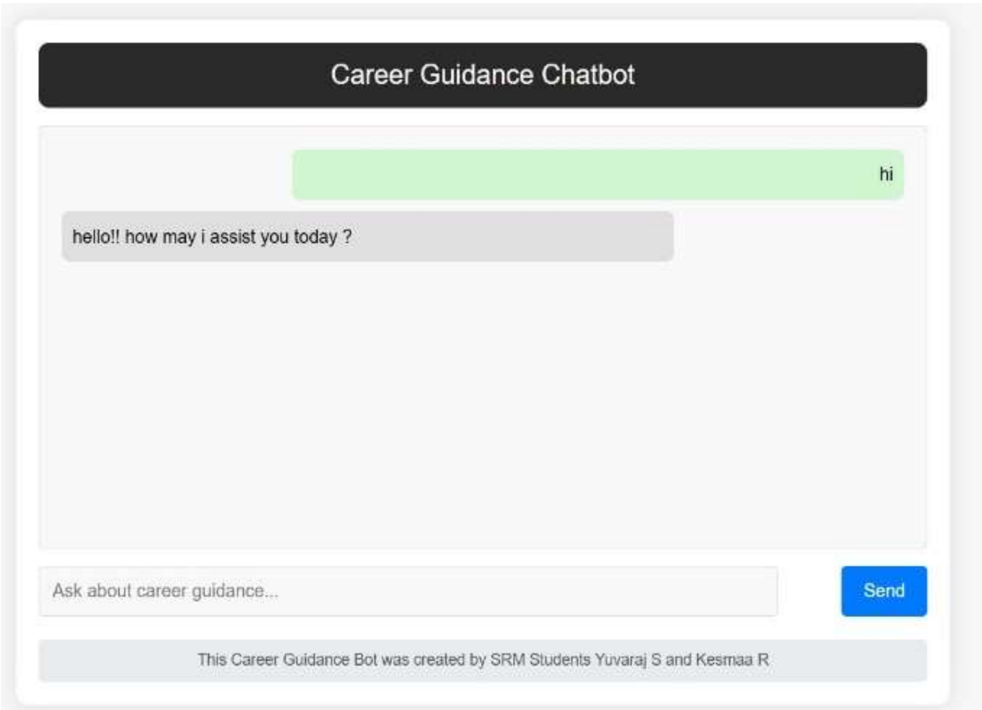

Fig.1. Career Guidance System.

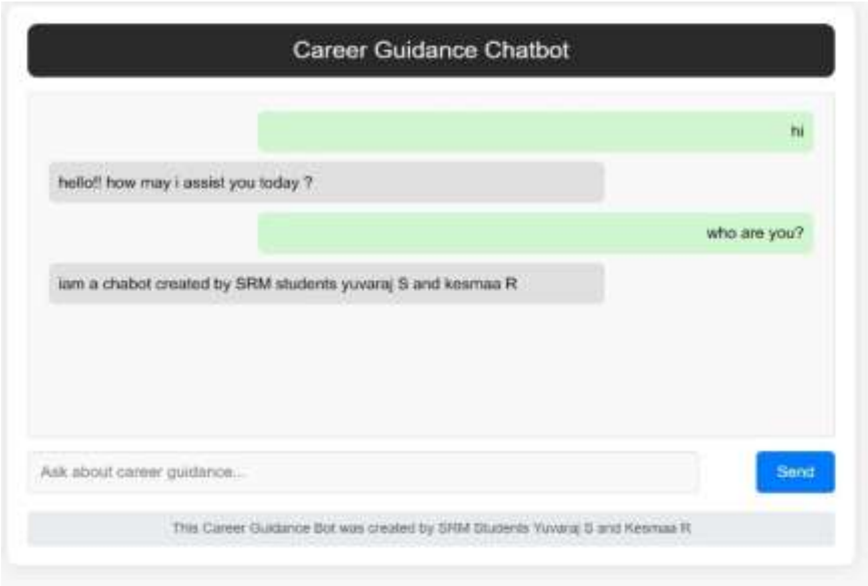

Fig. 2. Sample Query for Chatbot.

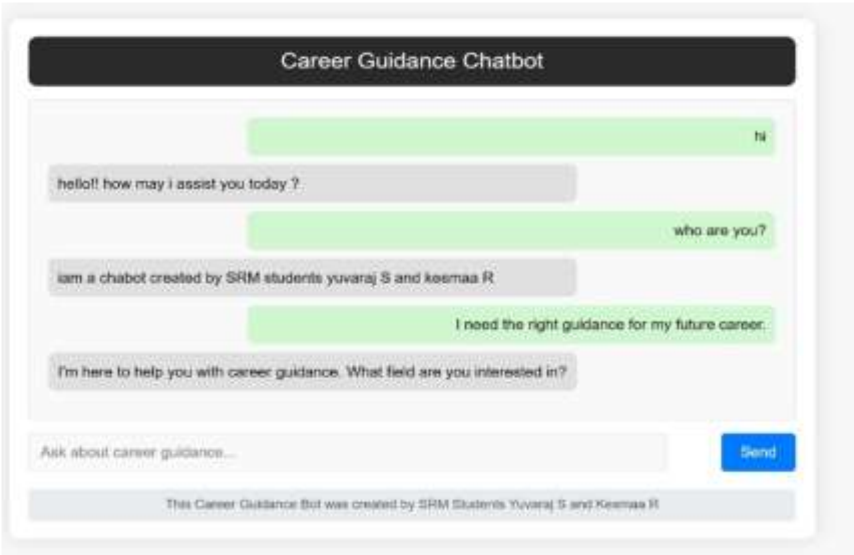

Fig. 3. Complex Query in Chatbot.

In the Figure 1,2,3 show working Model CHATBOT for Career guidance. Table 1 gives the information about the performance metrics.

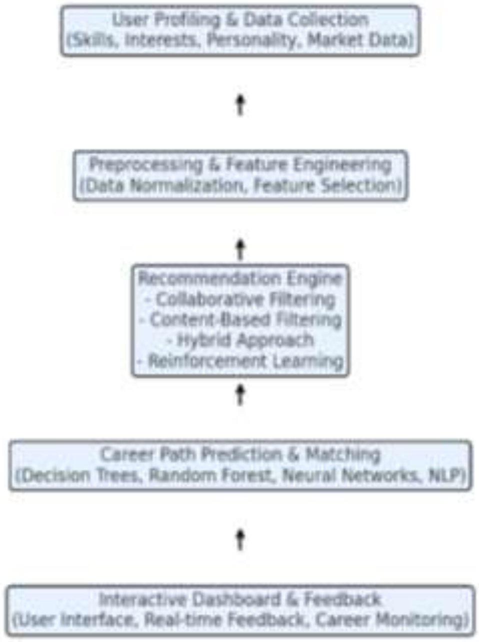

Fig. 4. System Architecture Workflow Diagram.

In the Figure 4 show System Architecture Workflow Diagram.

Quantitative Results

- Recommendation Accuracy: The hybrid recommendation model achieved an accuracy rate of **89.3%**, outperforming standalone collaborative filtering (82.5%) and content-based filtering (78.9%).

Satisfaction Ratings:

- 76% of participants rated the system as satisfactory or very satisfactory.
- 82% reported that the personalized dashboards improved their understanding of career options.
- 70% found the simulation feature useful for exploring alternative career pathways.
- Counsellor Validation: Career advisors agreed with 85% of the system's recommendations, indicating alignment between AI-driven and expert advice.

Table 1. Performance Metric Table

Metric	Hybrid Model	Collaborative Filtering	Content-Based Filtering
Accuracy (%)	89.3	82.5	78.9
Precision (Top-3 matches) (%)	84.7	79.2	73.5

Qualitative Results

Interviews and survey responses revealed strong engagement:

- “The dashboard clearly showed me which skills I need to work on to reach my career goals.” (Student, Age 19)
- “I liked the what-if simulation — it gave me confidence to choose between two career paths.” (Student, Age 21)
- “The system saved time in counselling sessions; it highlighted options that I could validate or refine quickly.” (Career Advisor)
- Some participants suggested improvements:
- Greater support for non-technical careers (arts, humanities).
- More flexibility for mid-career professionals considering a career shift.

The findings demonstrate that the Enhanced Career Guidance System is not only technically feasible but also effective in real-world application. The hybrid AI model provided more reliable career matches than traditional methods. Interactive dashboards and simulations significantly improved student understanding of career trajectories. As shown in Fig. 5, the Career Dashboard provides a visual overview of recommended career paths, radar-chart-based skill assessment, and the user’s career growth index. The integrated User Profile Page (Fig. 6) allows individuals to review psychometric results and academic achievements used by the system for recommendation generation. The Simulation and Feedback Panel (Fig. 7) further enables interactive “what-if” analysis, linking user feedback to reinforcement-learning updates for adaptive guidance.

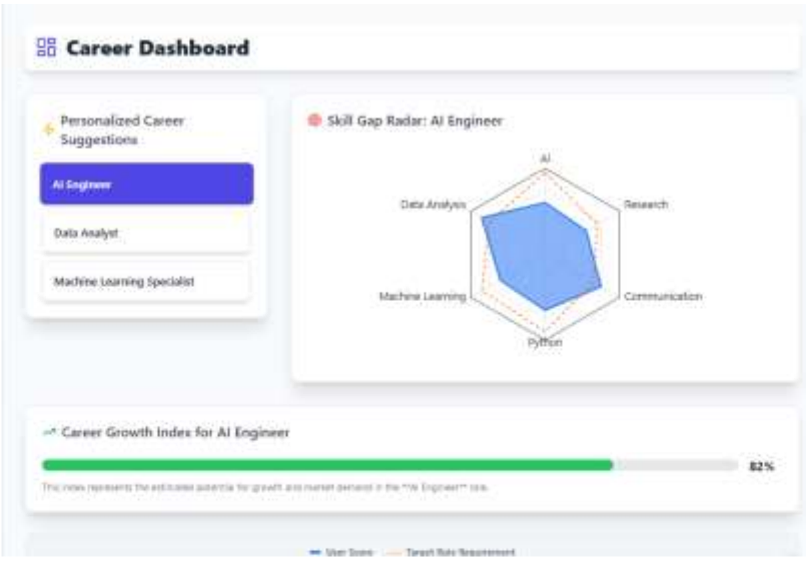

Fig.5. Career Dashboard Interface.

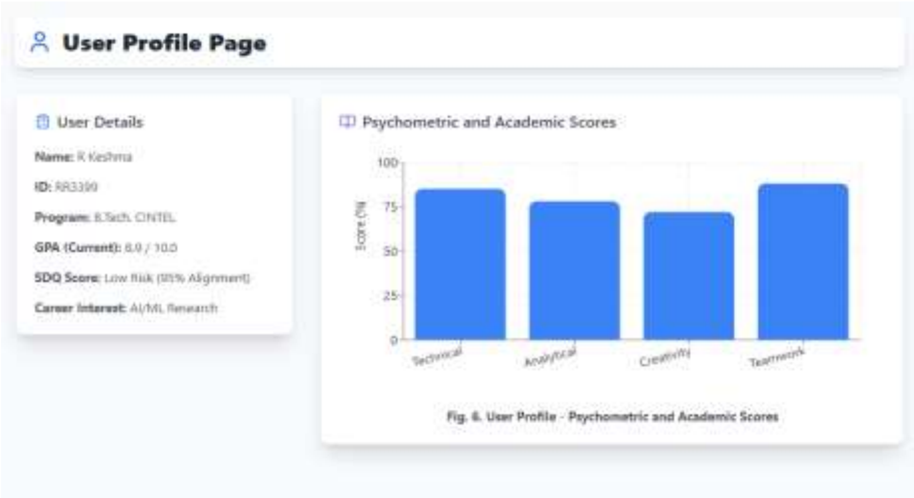

Fig.6. User Profile Page.

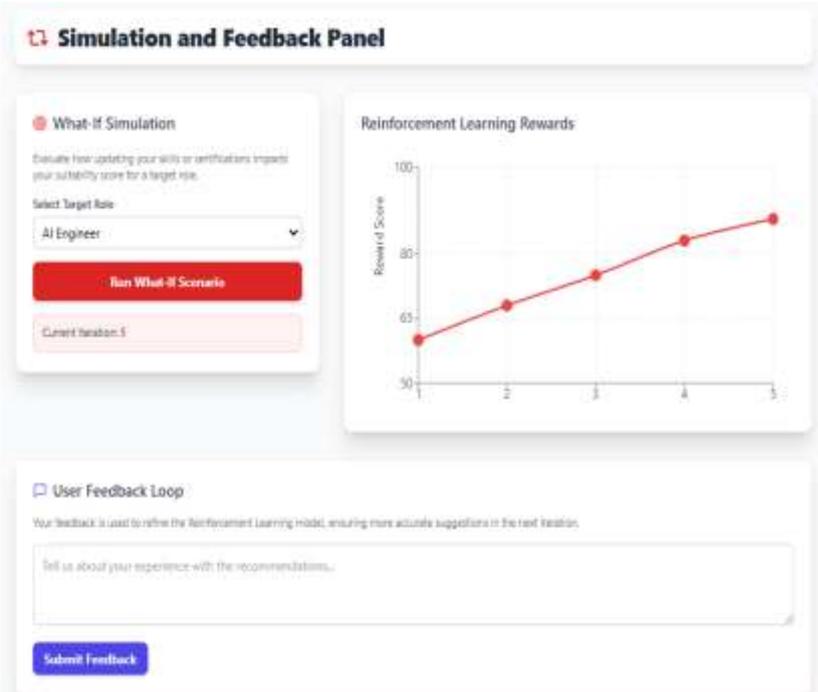

Fig.7. Simulation and Feedback Panel.

However, the study also highlighted limitations: a relatively small participant pool, lack of longitudinal tracking beyond three months, and limited industry coverage outside STEM fields. Addressing these gaps in future iterations will increase generalizability and inclusivity.

7 Conclusions

The proposed AI-driven career guidance system represents a significant advancement over traditional methods, offering dynamic, personalized, and real-time career recommendations. By integrating machine learning, psychometric assessments, and real-time market data, the system provides users with tailored guidance for informed career decision-making. It offers the potential to reshape how career paths are planned, ensuring more effective career development and satisfaction. Future enhancements will include support for additional industries, improved diversity and inclusion features, and more sophisticated AI models to further enhance prediction accuracy.

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